LA-UR-19-23165
Approved for public release; distribution is unlimited.

Title: LANSCE Diagnostic Robot Localization

Author(s): Watkins, Heath Andrew
Montoya, Lucas Sigfredo

Intended for: Masters Thesis Presentation

Issued: 2019-04-08

LANSCE Diagnostic Robot Localization

April 15, 2019

Thesis Committee

- Christopher Hall
  - Committee Chair, UNM Faculty
- Svetlana Poroseva
  - Committee Member, UNM Faculty
- Meeko Oishi
  - Committee Member, UNM Faculty

In Partial Fulfillment of the Requirements for the Degree

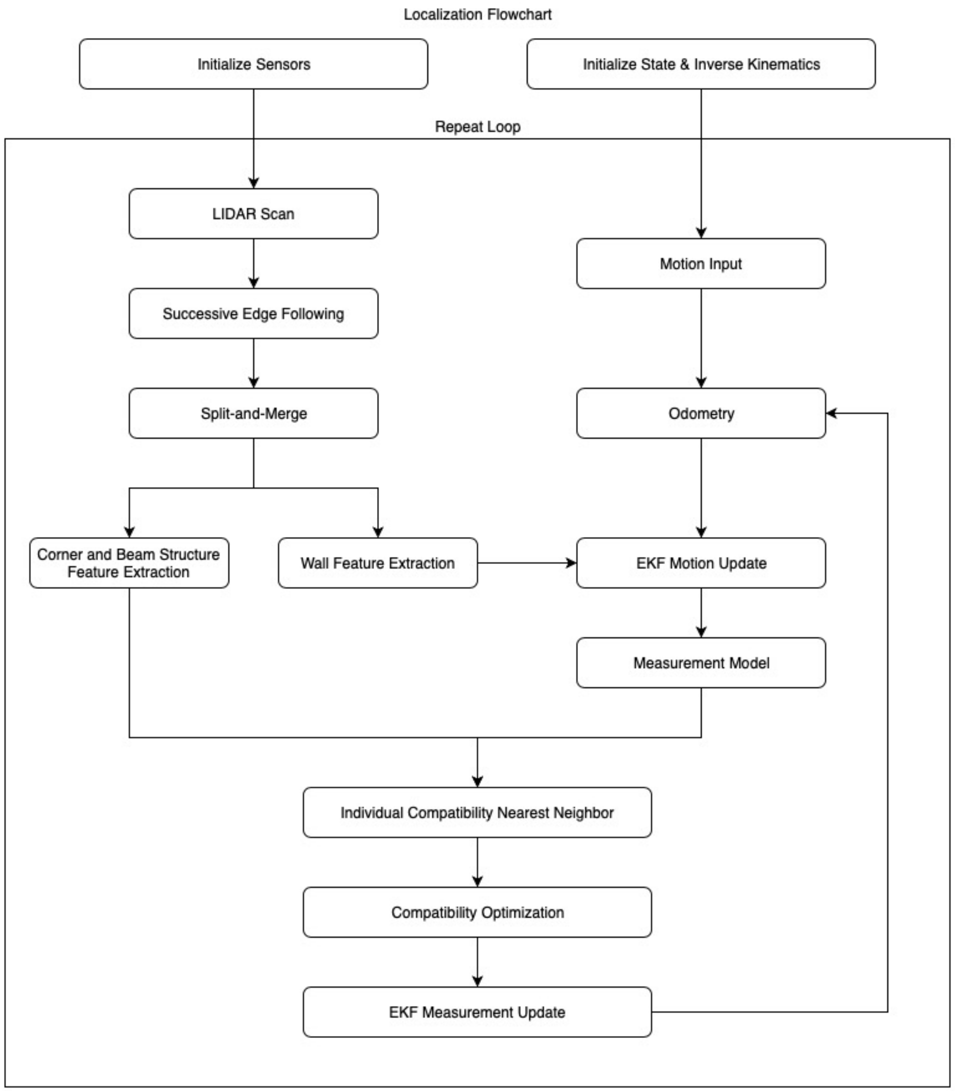
Master of Science in Mechanical Engineering

By Lucas S. Montoya

Spring 2019

Overview

- Motivation
- Background
- Vehicle Model
- Landmark Acquisition
- Localization
- Simulation
- Conclusion
- Future Work



Motivation

- Add beam diagnostics capability, providing previously unknown measurements of accelerator such as thermal imaging and radiation measurements
- Provide test bed for fully autonomous mode for mobile robot, proving feasibility for autonomy

Background

- Autonomous Mobile Robots
  - Motion
  - Sensor perception
  - Localization
    - Environment: structured/unstructured
    - Map type: feature/grid/topological
    - Landmark density
  - Navigation
  - Obstacle avoidance
- LANSCE linear accelerator facility, 800 MeV proton beam
  - ¾ mile long LINAC
  - Radiation produced by proton interactions

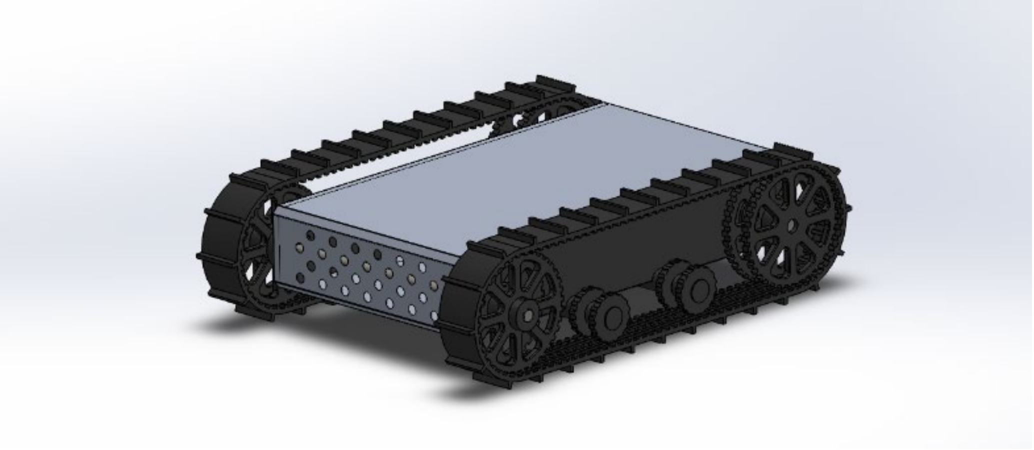
K.F. Schoenberg and P.W. Lisowski, "LANSCE A Key Facility for National Science and Defense," *Los Alamos Science*, no. 30, 2006.

Vehicle Model

- Chassis
  - Sensors
- Inverse Kinematics
  - Constraints
  - Model
- Odometry
  - Position estimation using motor encoders

Robot Chassis

- Dr. Robot Chassis
  - Tracked differential drive
  - Two 24V, 2.75A DC motors coupled with magnetic encoders
  - H 7” X W 21” X L 25.2”



Sensors

- Hokuyo URG-04LX-UG01 LIDAR
  - 4m, 240° sensor detectable range
  - 0.36° angular resolution
  - 10 Hz scan rate
  - Simulation suite contains Hokuyo LIDAR model
- Magnetic Encoders
  - Simulated sensors output angular position

Kamitani, Maeda, Mori, and Yamamoto, “Scanning Laser Range Finder URG-04LX-UG01 Specifications,” *Hokuyo Automatic Co. LTD*, June 2009.

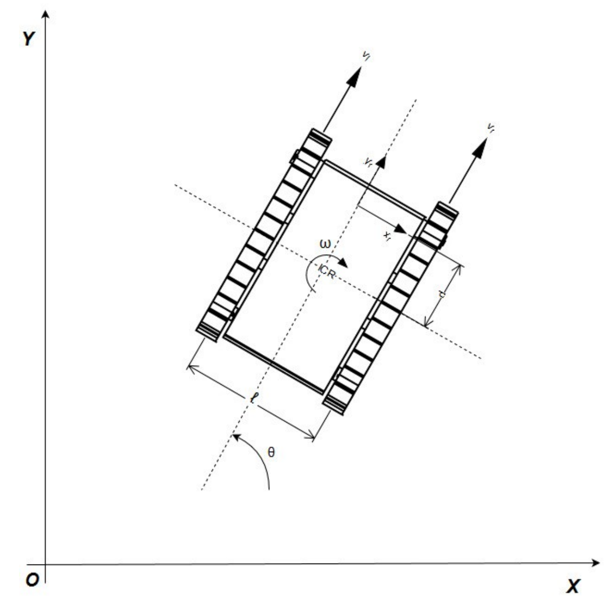
Inverse Kinematics: Constraints

- Track velocity

$$\begin{bmatrix} v_R \\ v_L \end{bmatrix} = \begin{bmatrix} r\dot{\varphi}_R \\ r\dot{\varphi}_L \end{bmatrix}$$

- Lateral motion limitation

$$W(X)\dot{X} = [\sin\theta \quad -\cos\theta \quad 0]\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = 0;$$



A. Kelly, *Mobile Robotics Mathematics, Models, and Methods*, Cambridge University Press, 2014.

R. Dhaouadi and A.A. Hateb, "Dynamic Modelling of Differential Drive Mobile Robots using Lagrange and Newton-Euler Methodologies: A Unified Framework," *Advances in Robotics and Automation,* vol. 2, 2013.

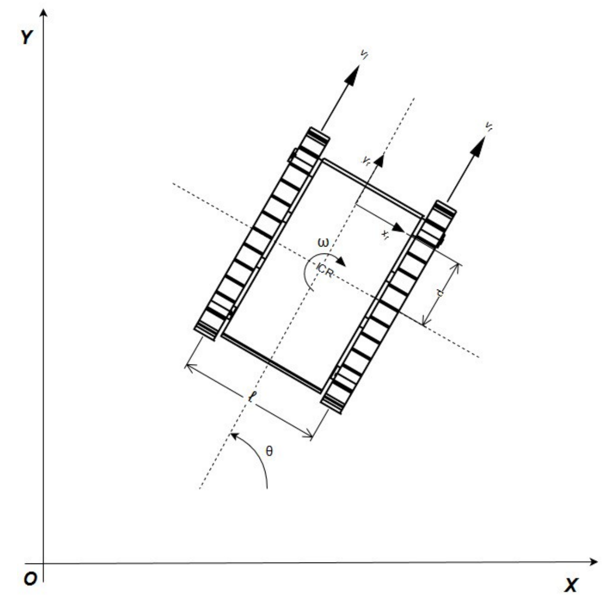
Inverse Kinematics: Model

- Motor velocity function

$$(\dot{\varphi}_R, \dot{\varphi}_L) = f(\dot{x}, \dot{y}, \dot{\theta}, g, r, l)$$

- Robot frame to track velocity

$$\begin{bmatrix} v_R \\ v_L \end{bmatrix} = \begin{bmatrix} \dot{y} + \dot{\theta}\dfrac{l}{2} \\ \dot{y} - \dot{\theta}\dfrac{l}{2} \end{bmatrix} = \begin{bmatrix} 1 & \dfrac{l}{2} \\ 1 & -\dfrac{l}{2} \end{bmatrix} \begin{bmatrix} \dot{y} \\ \dot{\theta} \end{bmatrix}$$



- Track to motor angular velocities

$$\begin{bmatrix} \dot{\varphi}_R \\ \dot{\varphi}_L \end{bmatrix} = \begin{bmatrix} g\dfrac{v_R}{r} \\ g\dfrac{v_L}{r} \end{bmatrix}$$

Where:

$\dot{\varphi}$ = motor angular velocity

r = cog radius

g = gear ratio

l = track distance

A. Kelly, *Mobile Robotics Mathematics, Models, and Methods*, Cambridge University Press, 2014.

Odometry: Displacement

- Track Displacement

$$\begin{bmatrix} \Delta s_r \\ \Delta s_l \end{bmatrix} = \begin{bmatrix} \left(\frac{r\varphi_r}{g}\right)_n - \left(\frac{r\varphi_r}{g}\right)_{n-1} \\ \left(\frac{r\varphi_l}{g}\right)_n - \left(\frac{r\varphi_l}{g}\right)_{n-1} \end{bmatrix}$$

- Track to robot frame displacement

$$\Delta s = \frac{\Delta s_r + \Delta s_l}{2}$$

$$\Delta \theta = \frac{\Delta s_r - \Delta s_l}{2l}$$

R. Siegwart and I.R. Nourbakhsh, *Introduction to Autonomous Mobile Robotics,* Cambridge, Massachusetts: MIT Press, 2004.

Odometry: Cartesian Displacement

- Robot frame to Cartesian coordinates

$$\begin{bmatrix}\Delta x\\ \Delta y\\ \Delta\theta\end{bmatrix} = \begin{bmatrix}\Delta s * \cos\left(\theta + \dfrac{\Delta\theta}{2}\right)\\ \Delta s * \sin\left(\theta + \dfrac{\Delta\theta}{2}\right)\\ \dfrac{\Delta s_r - \Delta s_l}{2 * L}\end{bmatrix}$$

- ICR offset correction

$$\begin{bmatrix}x\\ y\\ \theta\end{bmatrix} = \begin{bmatrix}x_{n-1} + \left((d\cos\theta)_n - (d\cos\theta)_{n-1}\right)\\ y_{n-1} + \left((d\sin\theta)_n - (d\sin\theta)_{n-1}\right)\\ \theta\end{bmatrix}$$

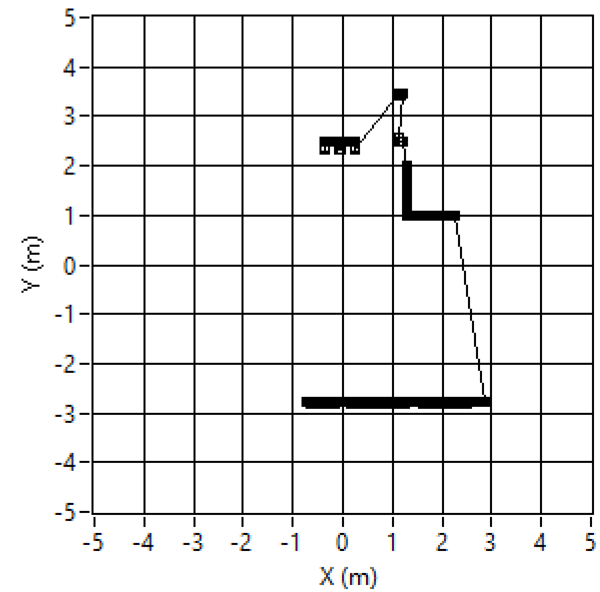
J.L. Crowley and P. Reignier, "Asynchronous Control of Rotation and Translation for a Robot Vehicle," *Journal of Robotics and Autonomous Systems,* Feb. 1993.

Landmark Acquisition

- Landmark selection
- Line extraction
  - Successive Edge Following
  - Split and Merge
- Feature extraction
  - Corner feature extraction
  - Beam structure feature extraction
  - Wall feature extraction

Line Extraction

- LIDAR point cloud raw scan
- Remove extraneous points
- Successive Edge Following
- Split-and-Merge



Successive Edge Following

- Euclidean distance between adjacent points

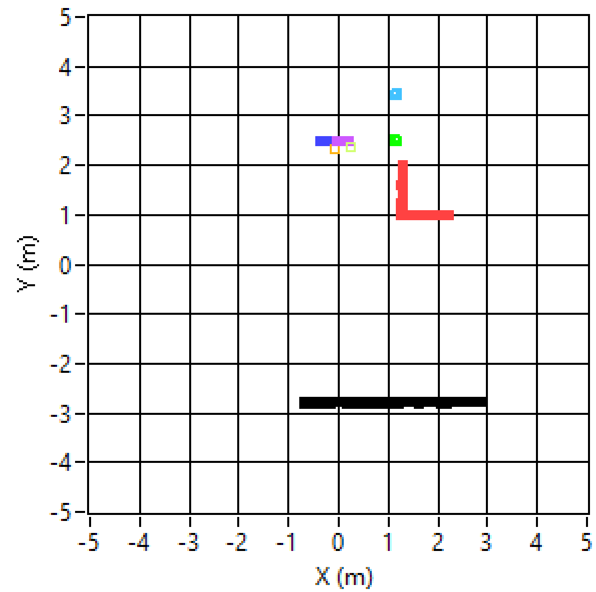
$$D(i, i+1) = \sqrt{(x_i - x_{i+1})^2 (y_i - y_{i+1})^2}$$

- Adaptive threshold

$$\bar{r} = \frac{\sum_{i=1}^{n} r_i}{n}; \quad \Delta D = k\bar{r}$$

- Segmentation criteria

$$f(k; j; 0,1) = \begin{cases} D(i, i+1) < \Delta D; & [x_i, y_i], j+1 \\ D(i, i+1) \geq \Delta D; & k+1, j=0 \end{cases}$$



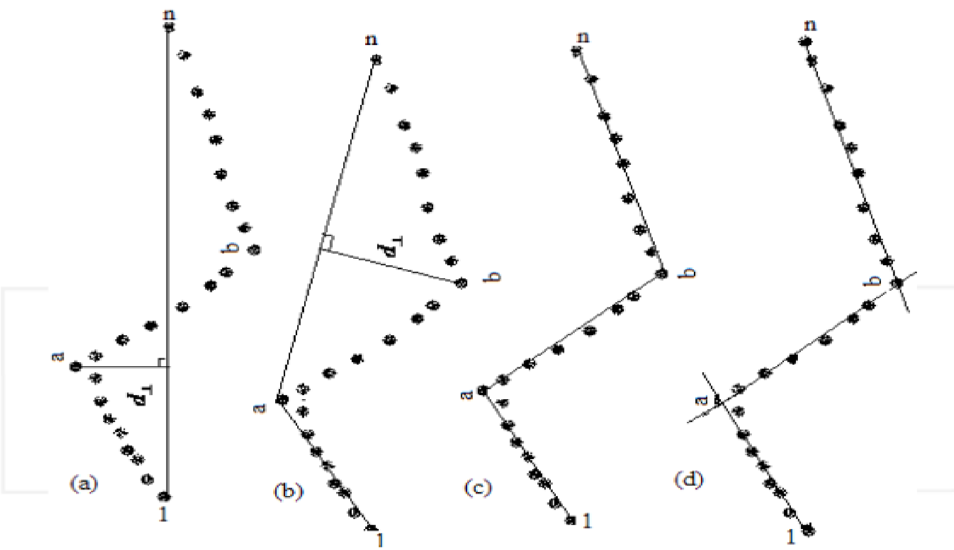
A. Siadat, A. Kaske, S. Klausmann, M. Dufaut, and R. Husson, "An Optimized Segmentation Method for a 2D Laser Scanner Applied to Mobile Robot Navigation," *In Proceedings of the 3rd IFAC Symposium on Intelligent Components and Instruments for Control Applications,* 2007.

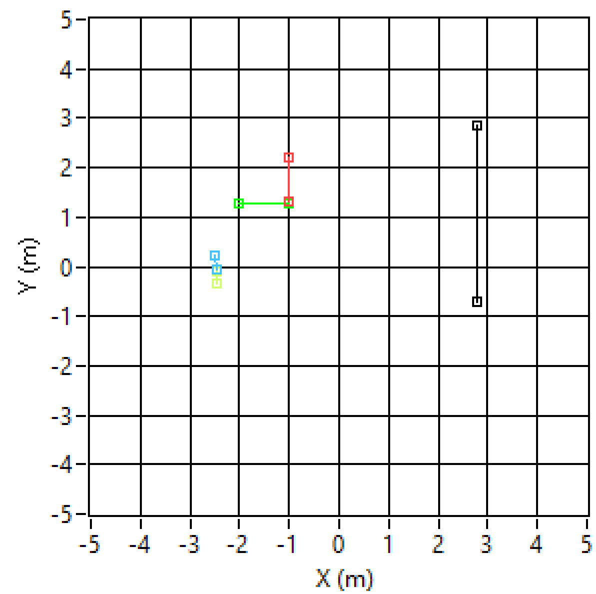
Y. Bu, H. Zhang, H. Wang, R. Liu, and K. Wang, "Two Dimensional Laser Feature Extraction Based on Improved Successive Edge Following," *Applied Optics*, May 2015.

Split and Merge

- Perpendicular distance

$$perp.dist. = \frac{|(y_2 - y_1)x_0 - (x_2 - x_1)y_0 + x_2 y_1 - y_2 x_1|}{\sqrt{(y_2 - y_1)^2 (x_2 - x_1)^2}}$$





V. Ngyen, A. Martinelli, N. Tomatis, and R. Siegwart, “A Comparison of Line Extraction Algorithms using 2D Laser Rangefinder for Indoor Mobile Robotics,” *In Proceedings of Conference on IROS 2005*, Edmonton, Canada, 2005.

M. Namoshe, O. Matsebe, and N. Tlale, “Feature Extraction: Techniques for Landmark Based Navigation System,” *Intech*, 2010.

Landmark Selection

- Repeatable, accurate, unique, static, and frequent

- Corner feature extraction
  - Orthogonality check
- Beam structure feature extraction
  - I-Beam
- Wall extraction
  - Robot bearing
  - Abbe error minimization

Corner Feature Extraction

- Orthogonality check, θ found by dot product

$$\vec{l}_n \cdot \vec{l}_{n+1} = \left\|\vec{l}_n\right\|\left\|\vec{l}_{n+1}\right\| \cos\theta$$

$$\theta = acos\left(\frac{\vec{l}_n \cdot \vec{l}_{n+1}}{\left\|\vec{l}_n\right\|\left\|\vec{l}_{n+1}\right\|}\right); \qquad 1.54\, rad \ \leq \theta \leq 1.6\, rad$$

- Line-Line intersection defined by determinants

$$X_x = \left(\frac{(x_1 y_2 - y_1 x_2)(x_3 - x_4) - (x_1 - x_2)(x_3 y_4 - y_3 x_4)}{(x_1 - x_2)(y_3 - y_4) - (y_1 - y_2)(x_3 - x_4)}\right)$$

$$X_y = \left(\frac{(x_1 y_2 - y_1 x_2)(y_3 - y_4) - (y_1 - y_2)(x_3 y_4 - y_3 x_4)}{(x_1 - x_2)(y_3 - y_4) - (y_1 - y_2)(x_3 - x_4)}\right)$$

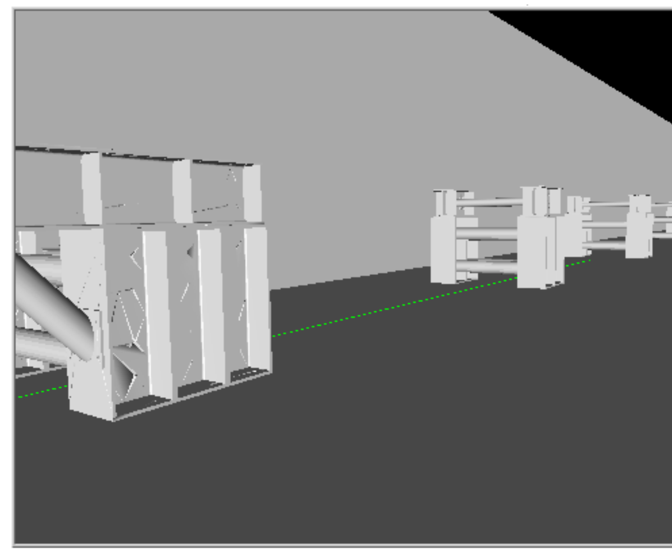
M. Namoshe, O. Matsebe, and N. Tlale, “Feature Extraction: Techniques for Landmark Based Navigation System,” *Intech*, 2010.

Beam Structure Feature Extraction

- Collinearity

$$\overrightarrow{AB} + \overrightarrow{BC} + \overrightarrow{CD} = \overrightarrow{AD}$$

- Length approximated, and midpoint is interpolated between line segments as landmark location



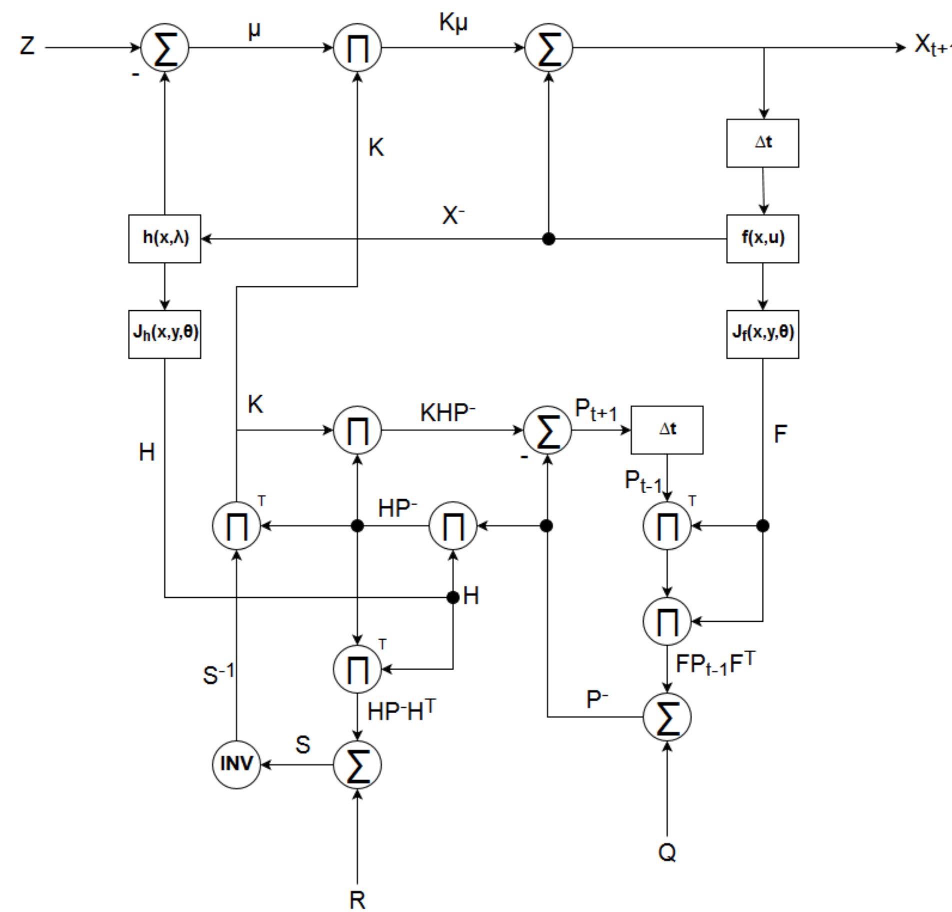
Wall Feature Extraction

- Abbe error accumulates over long distances
- Long, observable, unobstructed wall in beam tunnel
- Validation gates
  - World map position, must be greater than 3m from robot origin
  - Minimum 2m unbroken segment length
- Robot bearing calculated

$$\theta = atan2(y_2 - y_1, x_2 - x_1)$$

Localization

- Extended Kalman Filter
  - Linearizes state transition and measurement models
  - Map based estimator
  - Comprised of three steps:
    - Motion Update
    - Data Association
    - Measurement Update



EKF: Initialization

- State Matrix

$$X = \begin{bmatrix} x_r \\ y_r \\ \theta_r \\ x_i \\ y_i \end{bmatrix}$$

- Estimation Covariance Matrix P
  - 3+2n x 3+2n Identity matrix
  - Initially independent

S. Riisgaard and M.R. Blas, “Slam for Dummies,” *A Tutorial Approach to Simultaneous Localization and Mapping*, vol. 22, June, pp. 1-127, 2004.

Motion Update: State Transition

- Predicted State Transition Matrix

$$f(X,u) = X_{t+1}^{-} = \begin{bmatrix} x + \Delta x \\ y + \Delta y \\ \theta + \Delta\theta \end{bmatrix} = \begin{bmatrix} x + \Delta s\, cos\theta \\ y + \Delta s\, sin\theta \\ \theta + \Delta\theta \end{bmatrix}$$

- Jacobian State Transition Matrix

$$F = J_f(x,y,\theta) = \begin{bmatrix} \frac{\delta X_1}{\delta x} & \frac{\delta X_1}{\delta y} & \frac{\delta X_1}{\delta\theta} \\ \frac{\delta X_2}{\delta x} & \frac{\delta X_2}{\delta y} & \frac{\delta X_2}{\delta\theta} \\ \frac{\delta X_3}{\delta x} & \frac{\delta X_3}{\delta y} & \frac{\delta X_3}{\delta\theta} \end{bmatrix} = \begin{bmatrix} 1 & 0 & -sin\theta\Delta s \\ 0 & 1 & cos\theta\Delta s \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\Delta y \\ 0 & 1 & \Delta x \\ 0 & 0 & 1 \end{bmatrix}$$

- Process Noise

$$Q = WCW^T = \begin{bmatrix} C\ \Delta x^2 & C\ \Delta x\Delta y & C\ \Delta x\Delta\theta \\ C\ \Delta y\Delta x & C\ \Delta y^2 & C\ \Delta y\Delta\theta \\ C\ \Delta\theta\Delta y & C\ \Delta\theta\Delta y & C\ \Delta\theta^2 \end{bmatrix}; where\ W = \begin{bmatrix} \Delta x \\ \Delta y \\ \Delta\theta \end{bmatrix}$$

S. Riisgaard and M.R. Blas, "Slam for Dummies," *A Tutorial Approach to Simultaneous Localization and Mapping*, vol. 22, June, pp. 1-127, 2004.

L. Chen, H. Hu, and K. McDonald-Maier, "EKF Based Mobile Robot Localization," *Emerging Security Technologies (EST) Third Internationl Conference*, Sept. 2012.

Motion Update: Error Covariance

- Robot Estimation Error Covariance

$$P^{rr} = FPF + Q$$

- Robot-Landmark Estimation Error Covariance

$$P^{ri} = FP^{ri}$$

- Estimation Error Covariance Matrix

$$P = \begin{bmatrix} P^{rr} & P^{ri} \\ P^{ir} & P^{ii} \end{bmatrix}; where\ P^{ii}\ is\ landamark\ covariance$$

N.A. Othman and H. Ahmad, "The Analysis of Covariance Matrix for Kalman Filter Based SLAM with Intermittent Measurement," *Proceedings of the 2013 International Conference on Systems, Control and Informatics*, 2013.

Data Association

- Individual Compatibility Nearest Neighbor
  - Uses Mahalonobis Distance and Chi-Squared distribution for compatibility
  - Mahalonobis distance accounts for covariance between variables, directional variance, and reduces to Euclidean distance if uncorrelated
- Compatibility Optimization
  - Reconsiders associations, if there are more than one possible hypothesis
  - Chooses “best” hypothesis

P.C. Mahalanobis, “On the Generalized Distance in Statistics,” *In Proceedings of the National Institute of Sciences of India,* vol. 2, 1936.

ICNN: Measurement Model

- Range/Bearing Measurement Model

$$h = \begin{bmatrix} range \\ bearing \end{bmatrix} = \begin{bmatrix} \sqrt{(\lambda_x - x)^2 + \left(\lambda_y - y\right)^2} \\ \tan^{-1}\left(\frac{\lambda_y - y}{\lambda_x - x}\right) - \theta \end{bmatrix}$$

Where, (λ_x, λ_y) are landmark locations

- Jacobian of Measurement Model

$$H = \begin{bmatrix} \frac{\delta r}{\delta x} & \frac{\delta r}{\delta y} & \frac{\delta r}{\delta \theta} \\ \frac{\delta b}{\delta x} & \frac{\delta b}{\delta y} & \frac{\delta b}{\delta \theta} \end{bmatrix} = \begin{bmatrix} \frac{x - \lambda_x}{r} & \frac{y - \lambda_y}{r} & 0 \\ \frac{\lambda_y - y}{r^2} & \frac{\lambda_x - x}{r^2} & -1 \end{bmatrix}$$

T.Bailey, J. Nieto, J. Guivant, M. Stevens, and E. Nebot, “Consistency of the EKF-SLAM Algorithm,” *Proceedings of the 2006 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Oct. 2006.

ICNN: Validation Gate

- Innovation μ, where z is LIDAR measurement

$$\mu = z - h$$

- Measurement Noise

$$R = \begin{bmatrix} rc & 0 \\ 0 & bd \end{bmatrix}$$

- Innovation Covariance

$$S = HPH^T + R$$

- Mahalonobis Distance

$$D_{ij}^2 = \mu^T S^{-1} \mu$$

- Chi-squared Distribution Validation Gate, with two degrees of freedom and 95% cumulative probability

$$D_{ij}^2 < \chi_{d,\alpha}^2$$

P.C. Mahalanobis, “On the Generalized Distance in Statistics,” *In Proceedings of the National Institute of Sciences of India,* vol. 2, 1936.

Y. Bar-Shalom and T.E. Fortmann, *Tracking and Data Association*, Academic Press In., 1988.

J. Neira and J.D. Tardos, “Data Association in Stochastic Mapping using the Joint Compatibility Test,” *IEEE Transactions on Robotics and Automation*, vol. 17, Issue 6, pp 890 – 897, Dec. 2001.

Compatibility Optimization

- Reconsiders associations if there is more than one feature associated with a single landmark
- Minimum Maholonobis distance is taken to be correct feature from set of features considered for single landmark
- Necessary primarily for beam structure features as there are multiple in close proximity

Measurement Update

- Kalman Gain

$$K = P^{-}H^{T}(S)^{-1}$$

- Robot State Update

$$X_{t+1} = X_{t+1}^{-} + K\mu$$

- Error Covariance Update

$$P_{t+1} = (I - KH)P^{-}$$

- Entire process repeated for each observed and associated feature

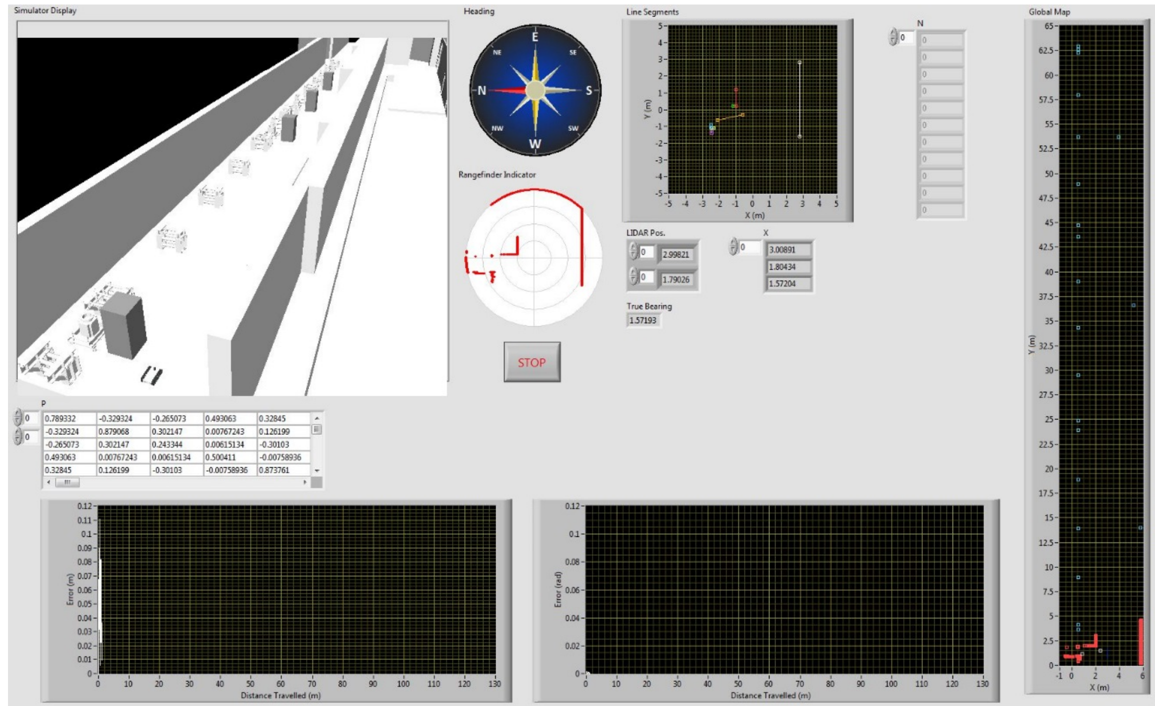
S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*, Cambridge, Massachusetts: MIT Press, 2006.

H. Durrant-Whyte and T. Bailey, “Simultaneous Localization and Mapping,” *IEEE Robotics & Automation,* June 2006.

M.R. Nepali, D.A.H. Prasad, S. Balasubramaniam, V. EN, and Ashutosh, “A Simple Integrative Solution for Simultaneous Localization and Mapping,” *International Journal of Robotics and Automation,* vol. 5, Issue 2, 2014.

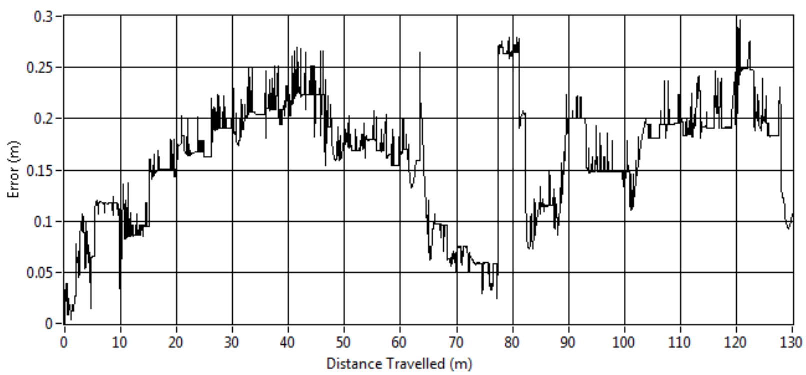
LabVIEW Robotics Simulation

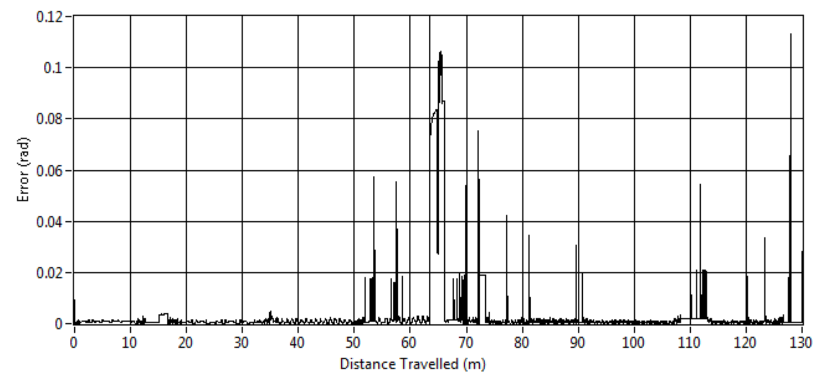
- Based on Open Dynamics Engine
- CAD importer
- Robot model builder
- Environment simulator wizard

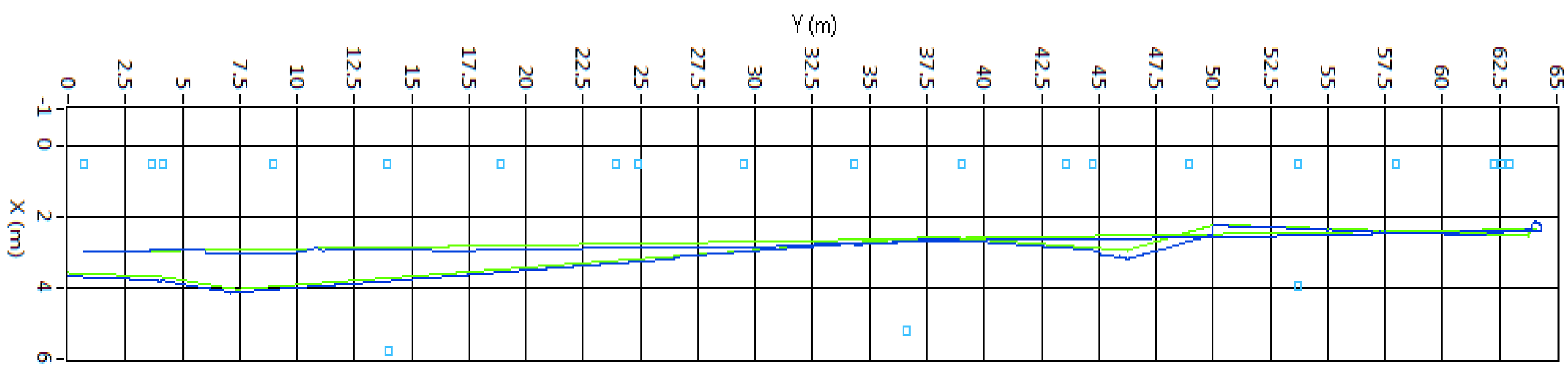


“Overview of the LabVIEW Robotics Simulator,” *National instruments,* 22 December 2015, http://www.ni.com/white-paper/14133/en/

Simulation Results







Error Calculation

- Ground Truth Vs. Estimation

$$Error_p = \sqrt{(x_{r,e} - x_{gt})^2 + (y_{r,e} - y_{gt})^2}$$

$$Error_\theta = |\theta_{r,e} - \theta_{gt}|$$

L. Chen, H. Hu, and K. McDonald-Maier, "EKF Based Mobile Robot Localization," *Emerging Security Technologies (EST) Third Internationl Conference*, Sept. 2012.

Conclusion

- Given ideal conditions, localization of the robot can be realized within 0.3 meters and 0.1 radians in heading
- Robot is sensitive to Abbe error, wall was crucial in maintaining position without diverging

Future Work

- Beam tunnel experimentation using robot hardware
  - WLAN communication
  - Develop FPGA and Real Time code to support localization

- Facilitate full robot autonomy
  - Obstacle Avoidance
  - Navigation algorithm development

- Research additional diagnostic sensors to maximize the potential for providing substantial measurements to physicists

Thank you

Questions?